Skin Cancer Image Segmentation & Detection by using Unsupervised Neural Networks (UNN)
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1. ABSTRACT

Image Segmentation (IS) plays an important role in many important applications, especially image applications such as medical X-rays image (MXRI) and magnetic resonance imaging (MRI). This activity has an important role in solving many difficult problems, particularly for many chronic diseases, such as skin cancer. This paper we will build the way to segment the processing of magnetic resonance images (MRI) using Unsupervised neural network algorithm (UNNA). This method have two problems: first, the trained network takes a long time to extract the desired results called (Desired Output). The second is, the results obtained from the training process are not pure (Containing Noise) as a result of the training process. The 2D DWT can be applied on the learned Patterns there will be a denoise (noise reduction or removal) by handling all the sections resulting from the activity of the segmentation of magnetic resonance imaging. Unsupervised neural network like Kohenen Network take the resulting image and the process of being trained by the way its findings to the original images. There was a decrease training time and access to the results derived from the process is a good performance of the diagnosis of skin cancer patients.

Keywords-component; Skin cancer images segmentation (SCIS), Self-organization-unsupervised neural networks (SOUNN).
2. INTRODUCTION

Image Segmentation (IS) plays a key role in digital image processing and self-discover the details of objects in important areas. The magnetic resonance imaging used to examine cancer patients medical terms using the segmentation method to separate the parts of the disease as areas specific to be detailed discover of the disease as a measure the size of cancerous tissue and to identify areas of surgery for this disease. Segmentation method depends on several factors and differ from one application to another and depending on the type of application as a image and other factors. Where it does not have a way of segment fixed be applied to all types of medical images to give the same results (Desired Output). Segmentation process find the collections that correspond to the important regions in the Image. When it is separate regions related with each other in the input image, identifying areas for collections, the result are called pixel classification and the same collections are called classes.[1] Pixel classification is often a desirable goal in medical images, particularly when disconnected regions belonging to the same texture class need to be identified, figure (1) . Determination of the total number of classes K in pixel classification can be a difficult problem. Often, the value of K is assumed to be known.[1,2]. Labeling is the process of assigning a meaningful designation to each region or class and can be performed separately from segmentation.

Pixel classification methods classified into five categories:
(1) Thresholding approaches. (2) Classifiers. (3) Clustering approaches. (4) Artificial neural networks. (5) Markov random field models (MRFM). Markov models of images (MMI) help user to make better image restoration, image enhancement or image segmentation. However, using
segmentation methods based on Markov Random Field (MRF) models requires a huge computing power and quite a lot of time. [3]

![Figure 1](image)

**Figure (1) Different types of Skin Cancer:** (a) diameter (b) color (c) border (d) asymmetry

3. MATHEMATICAL MODEL

We model the texture class labels $X$ as a Markov Random Field (MRF) with a four-point nearest neighbor neighborhood system and probability mass function is defined as:

$$ P_x(x) = \frac{1}{z} \exp(-\sum \beta(x_r, x_s) - \sum \gamma(x_r)) \ldots \ldots (1) $$

Where $\{r, s\}$ belongs to $C$, Where $\beta$ and $\gamma x r$ are MRF model parameters, $z$ is a normalizing constant, $C$ is the collection of cliques for the MRF, and $t(m; n) = 0$, if $m = n$; $t(m; n) = 1$, if $m$ is not equal to $n$. We will assume that the pixels in the observed image $Y$ can be modeled as conditionally independent Gaussian random variables given the pixel labels $X$, and that the conditional probability density function of the pixel at location $r$ given $X$ depends only on the value of $X$ at the same pixel location [4].

The simple algorithm for the practical side in this paper is:

1. Start
2. Input Image
3. Analyze the image
4. Find the parameters of image
5. Applying ANN for Image Parameters
6. Compare: Neural Network result with DB Images
7. If image found then
8. Matching
9. Else
10. Goto 2
11. End

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4. UNN SELF-ORGANIZING MAP FOR PIXELS CLASSIFICATION

Artificial Neural Networks (ANNs) are parallel networks of processing elements (PE) or nodes that simulate biological learning. Each node in an Artificial Neural Networks can be performing Primary computations. Learning is achieved through the adaptation of weights assigned to the connections between nodes. ANNs represent a paradigm for machine learning and can be used in a variety of ways for (IS). The most widely applied use in medical imaging is as a classifier, where the weights are determined using training data, and the ANNs are then used to segment new data. Because of many interconnections used in a neural network, spatial information can easily be incorporated into its classification procedures. Self-organizing in networks is one of the most fascinating topics in the neural network field. In Self-organizing networks, the weights changed themselves at every learning step. The change depends up on the neighborhood of the input pattern and the probability pattern, with which the permissible input pattern is offered.

Neural Network can be classified as a network transfer of electrical signals from a higher dimension space to a one-way Unidirectional or two dimensional units neurons. The neural network of self-training organization of input and understandable data to the groups of similar patterns, according to the criterion of similarity. such as neural networks are able to discover the learning organization, as well as the connections between inputs and adjust their future response according to these inputs. Topographic representation of the neural network is to save relations between network inputs that are mapped in a manner where the inputs neighboring space entry is planned to neighboring Neurons in the space of the map. This is means that the process of activation will activate neurons neighboring . Thus, the neural network’s training (Unsupervised Training) are not under supervision during the learning process. [5]
UNN Kohonen is consider connecting weights between the elements of the sample spot entered for specific neurons such as the level is set at 2D(i, j). Here we can represent the weights vector values between Ni, j and Wi,j. The map preserves topological relationships between inputs in a way that neighboring inputs in the input space are mapped to neighboring neurons in the map space. In UNN Kohonen’s model, the neuron with minimum distance between its weight vector wij and the input vector X is first identified by using the following criterion.

\[ |X - W_{k,j}| - Mini \leq j < n(Mini \leq j < n |X - W_{i,j}|) \ldots\ldots (2) \]

After the (k, l)\textsuperscript{th} neuron in the 2-D plane is located, the weights of its neighboring neurons are adjusted by using the following:

\[ W_{ij}(t+1) = Wij(t) + \alpha |X - W_{ij}| \ldots\ldots (3) \]

until the weight vector reaches equilibrium, this is means:

\[ W_{ij}(t+1) = W_{ij}(t) \ldots\ldots (4) \]

We use a UNN(Unsupervised Neural Networks)like Kohonen self-organizing map for the unsupervised classification of pixels in head of magnetic resonance images, and that is focuses specifically on the classification of head scans in normal subjects. The main objectives of this application are below: (1) Measure the disease gland volume (2) Segment disease gland texture into gray matter, white matter, and cerebrospinal fluid (3) Delineate specific disease gland structures. Magnetic resonance images pixel classification (MRIPC) is achieved by using a UNN Kohonen self-organizing map to automatically cluster the pixel feature vectors. Feature space to be used for pixel classification consists of one or more of the three dimensions as follows [6]: (a) T1 weighted image. (b)T2 weighted image. (c) Proton density weighted image.
We use feature space consisted of T1 weighted image, T2 weighted image and Proton density weighted image to classify image pixel to 4 classes. The results achieved are satisfactory and are shown in Fig.3. Where, the size of every magnetic resonance images is 512*512 pixels. Topologies for the original neuron of UNN Kohonen self-organizing map use with 2-by-2 grids.
5. UNN SELF ORGANIZING ALGORITHM

(1) Randomize the map's nodes' weight vectors  
(2) Extract an input vector  
(3) Pass any node in the map:
  
  - a. Use Euclidean distance formula to find similarity between the input vector and the map's node's weight vector. The distance between two points in the plane with coordinates \((x, y)\) and \((a, b)\) is given by
    \[
    dist((x, y), (a, b)) = \sqrt{(x-a)^2 + (y-b)^2} \quad \cdots \cdots (6)
    \]

  Note that, the Euclidean Distance (ED) is the "ordinary" distance between two points that one would measure with a ruler, and is given by the Pythagorean formula. By using this formula as distance, Euclidean space (or even any inner product space) becomes a metric space. The Euclidean distance between points \(p\) and \(q\) is the length of the line segment \(pq\). In Cartesian coordinates, if \(p = (p_1, p_2, \ldots, p_n)\) and \(q = (q_1, q_2, \ldots, q_n)\) are two points in Euclidean n-space, then the distance from \(p\) to \(q\) is given by:
    \[
    d(p, q) = \sqrt{((p_1-q_1)^2 + (p_2-q_2)^2 + \cdots + (p_n-q_n)^2)} = \sqrt{\sum (p_i-q_i)^2} \quad \cdots \cdots (5)
    \]
  
  - b. Track the node that produces the smallest distance (this node is the best matching unit).

(4) Update the nodes in the neighborhood of BMU by pulling them closer to the input vector  
(5) Increment \(t\) and repeat from 2, while \(t < \lambda\). [6,7]

6. UNN CLASSIFICATION PIXEL BASED ON (IS)

The new preceding discussion may be summarized by the following procedures. We can discuss the following procedures:  
(1) UNN Kohonen self-organizing map is trained with P level approximation image.  
(2) Classify pixels of original image used above trained UNN Kohonen self-organizing map. We use feature space consisted of T1 weighted image, T2 weighted image and Proton density weighted image to classify image
pixel to 4 classes. T1 weighted image, T2 weighted image and Proton density weighted image.

7. CONCLUSIONS

Magnetic Resonance Image Segmentation (MRIS) is important but very difficult problem in medical image processing. In general, it can not be solved using traditional and simple techniques for image processing. This paper discusses the manner in which the image is not classified as controlled substances by using UNN map self-organization Kohonen. This technique is presented here showed a very encouraging level of performance for the division in the form of magnetic resonance imaging of the head. Attempt are made to reduce the amount of knowledge already being used, in order to preserve the style and the general as possible. This makes the approach worth serious consideration for further development as an automatic tool for image segmentation in medicine.

REFERENCES


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